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Ischemia detection using Isoelectric Energy Function

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ABSTRACT

A novel method has been proposed for the detection of ischemia using an isoelectric energy function (IEEF) resulting from ST segment deviations in ECG signals. The method consists of five stages: pre-processing, delineation, measurement of isoelectric energy, a beat characterization algorithm and detection of ischemia. The isoelectric energy threshold is used to differentiate ischemic beats from normal beats for ischemic episode detection. Then, ischemic episodes are classified as transmural or subendocardial. The method is validated for recordings of the annotated European ST-T database (EDB). The results show 98.12% average sensitivity (S_E) and 98.16% average specificity (S_P). These results are significantly better than those of existing methods cited in the literature. The advantage of the proposed method includes simplicity, ruggedness and automatic discarding of noisy beats.

1. Introduction

In recent years, epidemiological transition due to obesity, smoking, tobacco use, physical inactivity, an unhealthy diet and harmful use of alcohol has increased the death rate. An estimated 17.5 million people died from cardiovascular diseases (CVDs) in 2012, representing 31% of all global deaths. Of these deaths, an estimated 7.4 million were due to coronary heart disease and 6.7 million were due to stroke. Out of the 16 million deaths under the age of 70 due to non-communicable diseases, 82% for low and middle-income countries and 37% are caused by CVDs. As per prediction of the world health organization (WHO), 75% of world deaths will be due to non-communicable and coronary heart diseases (CHD) by 2030 [1]. These diseases mainly result from atherosclerosis and thrombosis, which can manifest as a coronary ischemic syndrome [2]. CVDs can be prevented by addressing behavioral risk and through management using medicine and early detection. So, currently, the attention of researchers is on establishing the timely and reliable detection of ischemia. An electrocardiogram (ECG) is one of the non-invasive techniques to diagnose the ischemia. An ECG is representative of the P wave (depolarization of the atria), QRS complex (depolarization of the ventricles) and T wave (ventricular repolarisation). Under normal conditions, an ECG carries a predictable duration, direction and amplitude of characteristic points. However, an ischemic ECG has a peculiar appearance, which is indicative of a decrease in terms of the availability of oxygen for cardiac tissues. ST-segment changes are produced by the flow of injury currents that are generated by the voltage gradients between the ischemic and non-ischemic myocardium during the plateau and resting phases of the ventricular action potential. This is manifested as an elevated or depressed ST segment in an ECG [3]. ST elevation usually appears in patients with transmural ischemia or prinzmetal angina while ST depression appears in subendocardal ischemia or stable or unstable angina [4]. A number of methods have been proposed in the last 10–15 years for the detection of ischemic beats and episodes based on digital signal analysis, rule based wavelet transforms and soft computing based algorithms. These include wavelet based entropy [5,6], a network self-organizing map (sNet-SOM) model [7], neural network (NN) and nonlinear principal component analysis (NLPCA) [8], a back propagation algorithm [9], Karhunen–Loeve transform (KLT) [10], a genetic algorithm [11], hidden Markov models (HMM) [12], machine learning techniques [13], decision tree rules using fuzzy models [14], vectorcardiographic ST-T [15] methods etc. These methods have the potential of a decision support system that can provide good advice for diagnosis. Other methods based on wavelets [16], an ant-miner algorithm [17], kernel density estimation (KDE) and support vector machine (SVM) [18], statistical features [19] and a fuzzy expert system through stochastic global optimization [20] are reported. These methods have a major advantage of interpretation of decisions as compared to black box approaches like neural networks. A Real-time system for the detection of myocardial infarction [21] is implemented. Similarly, one study identifies the ECG morphologies for normal and abnormal beats based on wavelet power spectra using statistical significance [22]. Likewise, a survey of ischemia detection techniques [23] has been performed. During recording of an ECG, the artifacts, i.e. anything other than the

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muscular activity of the heart, are contaminated on ECG. Critical problems contributing to poor detection and classification of the ST segment in an ECG include baseline wanders, varying ST-T patterns, muscle tremors, high frequency noises, power line interference, etc. The reasons may be the interference of alternating current, a loose electrode connection, patient movements, malfunctioning of the machine etc. [24]. These artifacts have an adverse effect on an ECG and make the automatic delineation of characteristic points more difficult. Besides these problems, it is necessary to detect ischemic episodes when a patient is in a critical care unit (CCU). An experienced cardiologist could easily diagnose the ischemia by just looking at the ECG, even with the presence of artifacts. However, the elimination of artifacts is primarily required to facilitate easy, accurate and automatic detection of the ST segment and classification of ischemic episodes in pathological cases. The recommendation of the American Heart Association (AHA) is to preserve the linear phase, and high pass filters can be designed with a cut-off frequency equal to the fundamental frequency of a heart rate of or lower than a certain threshold, i.e. 0.8 Hz. A number of filters have been designed for the correction of baseline wandering, including FIR and IIR filters. But these filters have the disadvantage that the ECG signal is deformed as the cut-off frequency increases. Cubic spline filters overcome this without the effect of deformation, but these filters make several errors when the sampling rate is low or when the baseline changes suddenly. Adaptive filters determine the signal and adaptively remove the noise uncorrelated with the deterministic signal. The disadvantage of these filters is the distortion of the ST segment [25]. Similarly, for ECG enhancement, the most widely used algorithm is the least mean square adaptive algorithm (LMS). But this algorithm is not able to track the rapidly varying non-stationary ECG signal within each heart beat. Using the method presented in this paper, all the listed problems can be avoided because a wavelet transform is found to be more suitable for a non-stationary ECG signal [26]. Due to the time–frequency resolution capability of wavelet transforms (WT), they were found to be more suitable for removal of noises and artifacts and for the delineation process in ECG records as compared to Fourier transform (FT) and short time Fourier transform methods (STFT) [27]. The general objective of this paper is to propose and validate a simple method for the detection of ischemia based on an isoelectric energy function through accurate pre-processing and detection of basic ECG characteristic points. Our contribution towards the diagnosis of ischemia is twofold. First, the proposed method could provide an interpretation of the results. This is of great importance while designing a device for medical decision support for patients in a critical care unit (CCU) without knowing past references. Second, it involves a direct analysis based on isoelectric energy without the involvement of any complicated calculations. The paper is organized in six sections: Section 1 introduces the ECG, ischemia and related work, Section 2 deals with resources and methods, Section 3 presents the methodology, Section 4 discusses the results, Section 5 makes a comparison with existing methods and Section 6 covers conclusions and the future scope.

2. Resources and methods

2.1. European ST-T database

Normal and ischemic (elevated and depressed) ECG records have been taken from the European ST-T database (EDB). EDB records are well characterized digital recordings of ECGs, which are used by most biomedical researchers for validation of their algorithms. The EDB contains 90 ECG signals for two hour recordings with a sampling frequency of 250 Hz per channel over a 10 mV range with 11-bit resolution [28]. The database contains records of two leads acquired from V_1, V_2, V_3, V_4 and V_5 and MLI and MLIII positions. The database records have been annotated by three expert cardiologists. The experts have diagnosed and marked the beginning and ending of ischemic episodes in the database itself. The present research work has been carried out on 43,876 ST segments from e0103, e0104, e0105, e0108, e0113, e0114, e0147, e0159, e0162 and e0206 recordings of this database.

2.2. Wavelet transform

The wavelet transform (WT) of a function $f(t)\ \varepsilon\ L^2(R)$ [29] at scale 'a' and position 'b' is represented by

$$\mathrm{Wf}(a,b)=\int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-b}{a}\right)(t)dt \tag{1}$$

Eq. (1) realizes that the signal to be analyzed $f(t)$, is convolved with a dilated version of the mother wavelet $\psi(t)$. WT is a linear operator that decomposes a signal $x(t)$ into frequency components appearing at different scales. Higher scales contain low frequency components while lower scales have higher frequency components of a decomposed signal. In a discrete time decomposition system, the wavelet coefficients are obtained by passing a vector x (n) through a bank of filters, namely approximation coefficients (CA) and detail coefficients (CD) [30]. For $a=2^J$, the wavelet transform is called a dyadic digital wavelet transform (DWT). In our case, it is a digitized ECG signal in the form of samples. The mallet algorithm [29] is used to compute DWT of a digital signal $f(n)$, as expressed in Eq. (2) and (3).

$$S_{2^j}f(n)=\sum h_k S_{2^{j-1}}f\left(n-2^{J-1}k\right) \tag{2}$$

$$W_{2^j}f(n)=\sum g_k W_{2^{j-1}}f\left(n-2^{J-1}k\right) \tag{3}$$

where $S_{2^0}f(n)=d(n), S_{2^j}$ is a smoothing operator and $W_{2^j}f(n)$ is the wavelet transform of the digital signal $f(n)$ to be analyzed. The high pass filter $G(w)$ and low pass filter $H(w)$ are further represented by coefficients $\sum g_k$ and $\sum h_k$ respectively.

$$G(w)=\sum g_k e^{-jkw} \text{ and } H(w)=\sum h_k e^{-jkw}$$

Orthogonal and compactly supported wavelets (daubechies, symlet and coiflets) are found to be more suitable for the analysis of non-stationary ECG signals because of their high number of vanishing moments [31].

3. Methodology

A general schematic diagram is shown in Fig. 1, also representing the methodology involved in the detection of ischemia for proposed method.

3.1. Pre-processing

The main goal of pre-processing is to formalize the accurate and efficient measurement of isoelectric energy in ST segments. Also, elimination of these noises is a very important task for the measurement of a TP and ST segment with high precision. It is very significant to recognize the artifact frequencies and to discriminate these artifact changes from genuine changes to prevent misdiagnosis. A general diagram corresponding to different frequencies is shown in Fig. 2. After discarding of wavelet coefficients

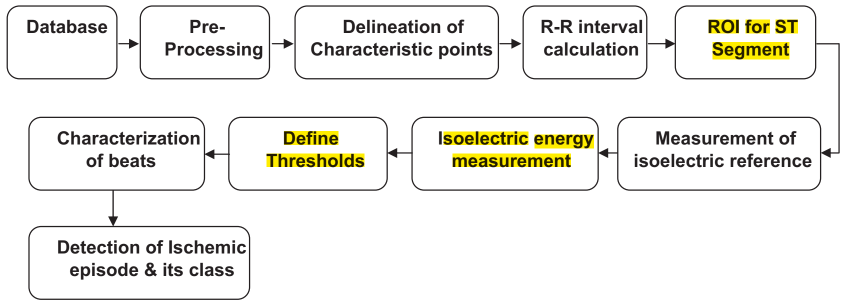

Fig. 1. Schematic diagram for proposed method.

corresponding to artifact frequencies of the original ECG signal, there should not be any destructive effects on the morphology of the original ECG signal. All records have been investigated for their 60 min duration. Further, the portion under investigation is broken into segments of one minute each.

3.1.1. Removal of baseline wanders

For removal of the DC drift (interpreted as TP segment voltage) in an ECG signal, a mean of one minute of ECG record samples is subtracted from the original ECG signal, and, for the removal of baseline drift (low frequency noise in the range of 0.5–1 Hz), the ECG signal is decomposed to the 8th level using a db4 wavelet transform. Thresholding is applied after this; it involves the discarding of approximation coefficients to zero at the 8th decomposition level followed by reconstruction [25,32]. The results in the elimination of baseline wanders in the e0105m record of EDB are shown in Fig. 3a.

3.1.2. Removal of muscle tremors

For elimination of this artifact (in the frequency range of 100–150 Hz), a baseline free ECG signal is further decomposed using the Coif4 wavelet function at the 1st level. The threshold value is calculated by estimating the noise level in the 1st level approximate coefficients. Then, a soft thresholding technique (Eq. 4) [26,33] is applied for the discarding of detail coefficients. Soft thresholding makes a coefficient value for X_{ds} smaller than the threshold value T to be zero, and T is subtracted from an analyzed signal x greater than T. The results of these noise removals in record e0105m of EDB are shown in Fig. 3b.

$$X_{ds} = \left\{ \begin{array}{cc} x-T & x>T \\ 0 & x \le T \\ x+T & x<-T \end{array} \right\} \tag{4}$$

3.1.3. Removal of power line interference (PLI)

A sine wave of 50 Hz frequency has been artificially added to the pre-processed ECG signal in order to exemplify the original ECG signal as contaminated with PLI. First, the ECG signal is decomposed using coif5 wavelet functions at the 2nd decomposition level. Then, the threshold value is deliberated by estimating the noise at the 2nd level. The hard thresholding technique (Eq. 5) [32,33] has been preferred by discarding the approximation coefficients. Hard thresholding makes all coefficients equal to zero for X_{dh} smaller than the threshold value T for analyzing signal x. The results in removal of PLI for the e0105m record of EDB are shown in Fig. 3c.

$$X_{\mathrm{dh}} = \left\{ \begin{array}{l} 0,\ x<T \\ x,\ x \ge T \end{array} \right\} \tag{5}$$

3.2. Delineation of characteristic points

Delineation implies starting with detecting the R peaks in an ECG signal. This is followed by defining windows around the detected R peak for identifying the QRS complex and other characteristic points, like the P wave, T wave, TP segment and ST segment. The multi-resolution wavelet transform, along with the window search method for local maxima and minima, has been employed [34,35]. First, the R wave is detected using threshold

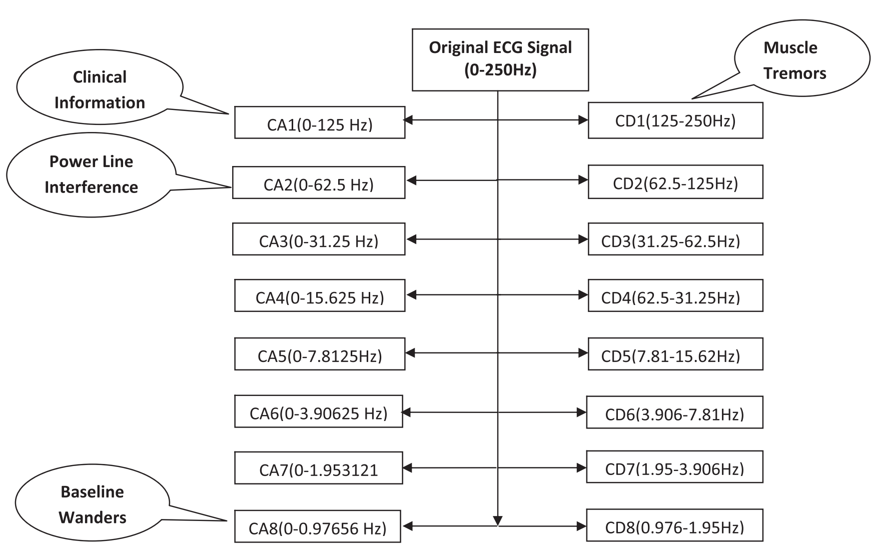

Fig. 2. Wavelet transform decomposition structure for relevant artifacts.

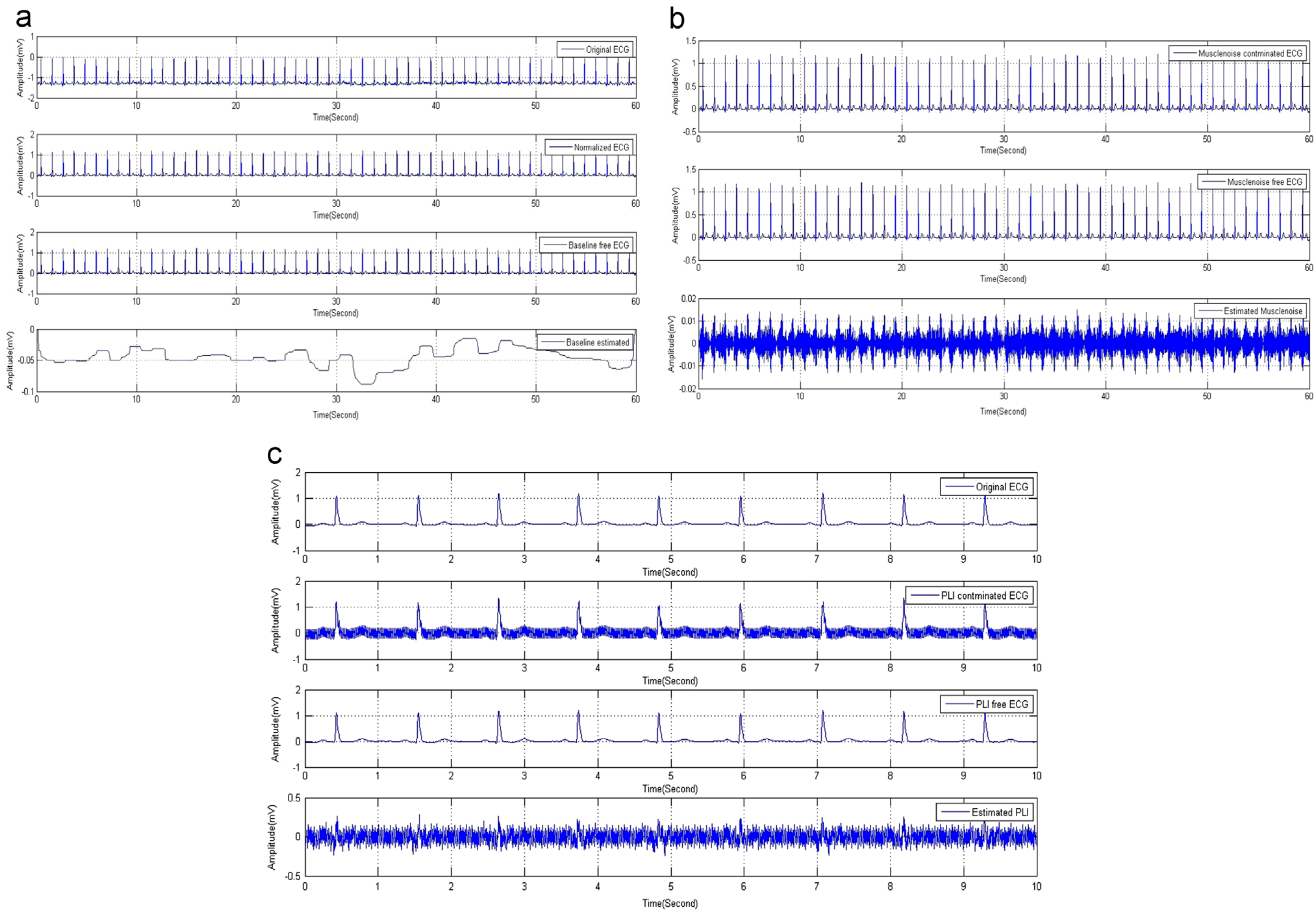

Fig. 3. (a) Results for removal of baseline wanders. (b) Results for removal of muscle tremors. (c) Results for removal of power line interference.

(ECG_max)*(ECG_amp) where ECG_max is the highest bump and ECG_amp=(ECG_max−ECG_mean)/2 is one minute the ECG record [36]. The time position and amplitude of each R peak is stored in R_INDEX. For P_INDEX, window[R_INDEX-400ms: R_INDEX-200ms] is searched for the local maximum while window [R_Index-200ms: R_INDEX-40ms] is employed for a local minimum for Q_INDEX. With a similar logic, a search for a local minimum in the window [R_INDEX+20ms: R_INDEX+100ms] for S_INDEX and a local maximum in window [R_INDEX+200ms: R_INDEX+400ms] for T_INDEX is employed. Fig. 4, '^' symbolizes the P, Q, R, S and T peaks for the e0105m record of EDB.

3.2.1. *Detection of onset and offset points*

For detection of the onset and offset points of each characteristic wave, the search is again initiated within the window for the corresponding INDEX to check the slope sign inversion [34,37,38]. The slope is computed by the expression of Newton's difference quotient as mentioned in Eq. (6). The window is taken as [INDEX-80ms: INDEX] for onset and [INDEX: INDEX+80ms] for offset.

$$\frac{f(x+h)-f(x)}{h} \tag{6}$$

An uncomplicated two point estimation calculates the slope of a nearby secant line through the points $(x, f(x))$ and $(x+h, f(x+h))$. Here, 'h' is taken as one sample interval. The consequent onset and offset points have a nearly zero or minimum slope. Then, the corresponding onset and offset sample values are stored in ON and OFF indices. Fig. 4 shows the onset and offset sample values represented by blue and black stars respectively.

3.3. *R-R interval calculation*

The R-R interval is the measurement of samples between two consequent R peaks in the ECG. The resting heart rate lies in between 60 to 100 beats per minute (bpm). Its normal duration is 0.6 to 1.2 s.

3.4. *Region of interest for the ST segment*

We have defined the region of interest corresponding to an ST segment (ROI_{ST}). This ROI has almost the same length of an ST segment as the criteria of pointJ, mentioned as

STS=R-R/8 (8th part of R-R interval samples)
ROI_{ST}= abs (Rpeak+3.2ms: STS)

3.5. *Measurement of the isoelectric reference (IR)*

The isoelectric reference (IR) is defined in the TP segment (Toffset: Ponset). This segment has a flat line between these two points; the voltage in this segment is nearly zero.

3.6. *Isoelectric energy measurement*

The isoelectric energy for each sample in the ST segment is measured; the proposed isoelectric energy function (IEEF) is

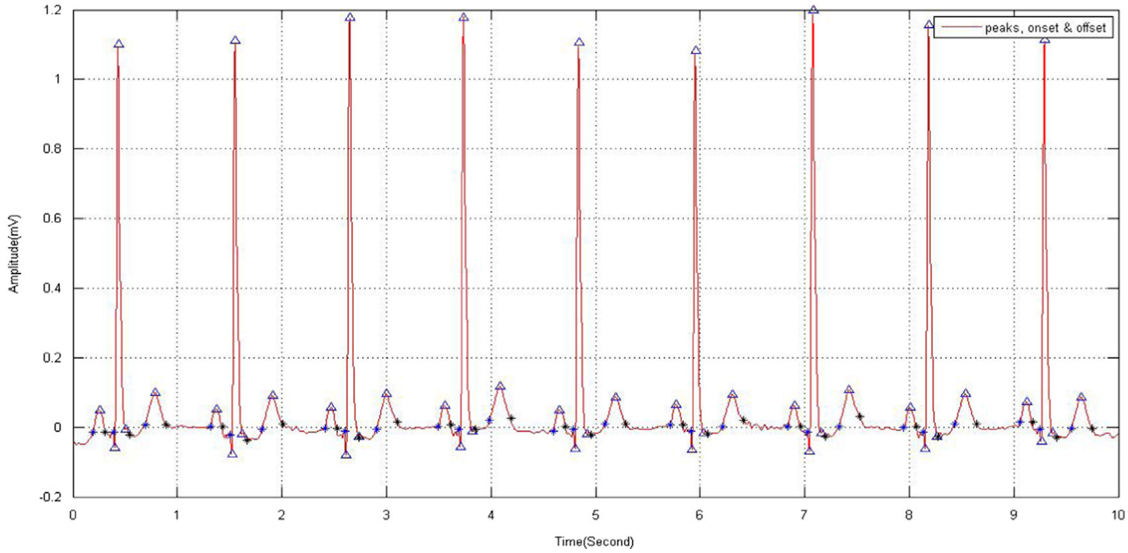

Fig. 4. Delineated characteristic points in pre-processed ECG. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

defined as presented in Eq. (7).

$$\mathbf{IEEF} = \frac{\sum\left[\left[(\mathbf{ST(i)}) - \mathbf{Avg(IR)}\right]^2 + \alpha\right]^{-1}}{\mathbf{Length(ST)}} * \beta \tag{7}$$

where i =1, 2, 3——————up to length of samples in an ST segment.

ST=voltage values for each sample of an individual ST segment in a record.
Avg (IR)=the average of voltages in isoelectric references in a record.
α= 0.01, artificially added constantly to prevent IEEF from acquiring an infinite value.
β is to keep the threshold for classification of the beat.
Length (ST) represents the number of samples in an individual ST segment in a record.

The IEEF is developed by keeping in view that the samples of the segments that are nearest to the isoelectric line will contribute more energy as compared to the samples far away from the isoelectric line. An alternate method to detect the elevation or depression of an ST segment with respect to isoelectric reference is to define a mathematical function that detects these deviations in a rugged manner. The main requirement of this function is that its value should increase as an ST segment hugs the isoelectric reference level while it should decrease as an ST segment tries to move away from the isoelectric reference. The motivation behind developing this function is a simpler but reliable threshold based classification for detecting myocardial ischemia.

3.7. *Defining thresholds*

After measurement of isoelectric energy for each ST segment in a particular record, we define the threshold to differentiate normal beats from ischemic beats in a record. A normal beat will always have more value of IEEF than will an ischemic (elevated or depressed) beat. Normal beats are annotated by 1 and ischemic beats are annotated by 0. This is called the preliminary stage.

Ischemic beat classification
If isoelectric energy ≥ 1
Then the beat is normal
Else the beat is ischemic

3.8. *Characterization of beats*

An ischemic beat characterization algorithm has been developed to filter out spurious ischemic or normal beats in a record after detecting all possible ischemic or normal beats in a record, called the final stage. Steps involved in the proposed algorithm are

1. The entire ECG record of 60 min is divided into 60 sections of one minute each.
2. Each section is de-noised and delineated, and each ST segment examined.
3. Each section with all its beats is properly identified and classified for being ischemic or normal.
4. Each beat is annotated as 1 if it is normal and annotated as 0 if it is ischemic.
5. All sections of the 60 min ECG record with annotations are recombined. The recombination gives an array of L entries where L is the numbers of beats in the 60 min ECG record. Each entry is either 0 (for an ischemic beat) or 1 (for a normal beat).
6. To implement an algorithm for the nth beat where $1 \leq n \leq$ L, the record has appended with four extra entries, i.e. two at the beginning and two at the end. The record now starts at -1 and ends at $L+2$. The extended array will have $[-1, 0, 1, 2, ----L, L+1, L+2]$.
7. The extended array is now filtered from $n=1$ to $n=L$ for spurious entries using the following algorithm

Let $S_n = \sum_{k=0}^{k=2} x(n+k)$
Where $x(n)=1$ for nth beat being normal
and $x(n)=0$ for nth beat being ischemic
If $S_n=3$, then $x(n)=1$
Else if $S_n=0$, then $x(n)=0$
Else let $P_n = \sum_{k=-2}^{k=0} x(n+k)$
    If $P_n=3$, then $x(n)=1$
    Else if $P_n=0$, then $x(n)=0$
        Else let $T_n = \sum(x(n-2), x(n-1), x(n+1), x(n+2))$

$T_n = 4$, then $x(n) = 1$
Else if $T_n = 0$, then $x(n) = 0$
Else $x(n) = 0.5$, beat is unclassified

3.9. *Detection of ischemia*

As per the advice of the European Society of Cardiology, the ischemic episode detection process should consider minimum 30-s duration of ECG signals. The search starts for the ischemic beats in an entire 60 min record. One ischemic episode that consists of at least 90% ischemic beats out of all beats for at least a 30 s duration or more in a record is named as an ischemic window.

Detection of ischemic episode

If [(No. of ischemic beats)/(All beats)] ≥ 90%)
The window is ischemic
Else The window is normal

3.10. *Artifact removal effects on the delineation process*

As mentioned earlier, artifacts have an adverse effect on the computerized analysis of ST segments in ECG signals. For example, baseline wanders have an adverse affect on ST segments; either ST segment depression or elevation can occur, which can further be misinterpreted as myocardial ischemia. Similarly, PLI introduces tall T-waveforms, which may be mis-identified in the measurement of R-R intervals (a basis of heart rate variability). Sometimes, muscle tremors overlap with the QRS complex, which may mimic atrial flutter or fibrillation [39]. To support the claim of the improved sensitivity of ischemia detection, normal ECG ST segments of the e0103m record from the European ST-T database were selected. A baseline wander of 0.25 Hz was superimposed to mimic the artifact of 1809 beats analyzed. 1186 beats were detected as normal, and the remaining 623 beats were detected as ischemic. Due to the false positive sensitivity, the normal signal reduces to 65.56%. On removing to this baseline wander using the proposed algorithm, the sensitivity attained again became 100%. This baseline removal alone can significantly improve the sensitivity in the case of computer aided ischemia detection.

4. Results and discussion

The pre-processing and delineation algorithms are implemented using the wavelet transform toolbox in MATLAB2012a. We have validated the proposed algorithm for 10 representative records of the annotated ESC ST-T database, namely the whole e0104 recording and the first hour of the e0103, e0105, e0108, e0113, e0114, e0147, e0159, e0162 and e0206 recordings. The selected ECG signals contain 20 ischemic ST segment episodes. These records covered both elevated and depressed ST segment cases. These records yielded a dataset of 43,876 cardiac beats as normal, ischemic or artifacts. After removing the artifacts and the mis-detected beats in the delineation process, the final dataset contained 43,762 ST segments to be diagnosed as normal or ischemic. We measured isoelectric energy for each sample in the ST segment using the proposed function and classified the beats as normal or ischemic in two stages. The philosophy of isoelectric energy is to form a function that has a high value if the ST segment is closer to the isoelectric line. This value would decrease as the ST segment moves either above or below the isoelectric line. The pre-processing will reduce the drift in the isoelectric line (TP segment) to nearly a zero value. We have measured isoelectric reference in the TP segment instead of PQ segments as high heart rate or conduction abnormalities may distort a PQ segment in some cases. To avoid the isoelectric energy function becoming infinite on account of zero in the denominator, an artificial constant (α) with a value of 0.01 has been added. For a normal ST segment, the value of IEEF lies in the range of 93.3–98.5, and, for an ischemic ST segment, its value lies in the range of 63.2–67.5. Hence, we define threshold β as 1/80. The length (ST) is the number of samples in an individual ST segment in a record; the length of an ST segment is adjusted according to the RR interval in a particular record. The function will contribute more energy for an ST segment that is horizontal or down sloping as compared to an up-sloping depressed ST segment. The proposed function has specifically been designed to classify the beats with a simple thresholding technique and, thus, does not require any training set. The most preferred terms for performance evaluation are sensitivity (S_E) and specificity (S_P), defined as

$$S_E = [\mathrm{TP}/(\mathrm{TP}+\mathrm{FN})] * 100 \quad (8)$$

$$S_P = [\mathrm{TN}/(\mathrm{TN}+\mathrm{FP})] * 100 \quad (9)$$

where TP denotes a true positive, FN denotes a false negative, TN presents a true negative and FP denotes a false positive detection as shown in Eqs. (8) and (9) respectively. Table 1 shows 98.12% average S_E and 98.16% average S_P for 10 representative ECG records of the annotated European ST-T database. The second stage beat characterization algorithm will filter out the spurious beats in records by checking annotated beats in the first stage. The advantage of the two-stage classification algorithms involves the automatic discarding of clinically irrelevant data, noisy beats. Then detection of ischemic episodes has been carried out. These 10 records have a total 20 ischemic episodes; the proposed algorithm successfully detects all episodes. After detection of all ischemic episodes, a class of detecting episodes has also been identified. We have identified the class of detecting ischemic episodes as subendocardial or transmural ischemia. As explained in earlier sections, depressed ST segments represent subendocardial ischemia while elevated ST segments represent transmural ischemia. To achieve this classification, we find the sample that lies in the middle of the ST segment. Its value is stored in ST_{mid}. Similarly, we identify the middle sample of the isoelectric reference segment. Its value is stored in IR_{mid}. It is obvious that, for transmural ischemia, $[\mathrm{ST}_{mid} - \mathrm{IR}_{mid}]$ shall be a positive value while this value shall be negative for subendocardial ischemia. Thus, knowing the value of $[\mathrm{ST}_{mid} - \mathrm{IR}_{mid}]$ helps us in identifying the ischemic beat and episodes as transmural or subendocardial ischemia. The total number of detecting episodes in a particular record and the corresponding class of an episode is shown in Table 2.

Table 1
Performance evaluation, comparison of proposed method with existing methods for European ST-T database.

Method	S_E (%)	$+S_P$ (%)
ANN and parametric modeling [42]	81	84
Rule based [45]	70	63
Multicriteria decision analysis [44]	91	91
Ant miner [17]	92.3	94.3
SVM [18]	95.7	95.3
KDE [18]	94.5	94.3
Fuzzy based [14]	91.2	90.9
GA & MCDA [11]	91.2	92.2
Statistical analysis [46]	97.83	97.56
Proposed method	**98.12**	**98.16**

Table 2
Detected class of ischemia for 10 representative records.

Sr. no.	Record no.	No. of ischemic episodes detected	Class of ischemia
1	e0103	4	Transmural
2	e0104	3	Transmural
3	e0105	3	Subendocardial
4	e0108	1	Subendocardial
5	e0113	1	Transmural
6	e0114	2	Transmural
7	e0147	3	Subendocardial
8	e0159	1	Subendocardial
9	e0162	1	Subendocardial
10	e0206	1	Transmural

5. Comparison with existing methods

This paper proposes a new function, named the isoelectric energy function for detection of ischemia, which does not involve any complex calculations. The performance of the algorithm has been validated on the above mentioned 10 records of the European ST-T database for comparison with existing methods. This database is used as a standard reference for classification of ischemic beats. Specifically, it was considered that every annotated episode in the database contained only ischemic beats. Our performance method cannot be judged against the mentioned methods [5–9,19,20,40,41] since either they were evaluated with other datasets or employed different performance measures or different databases. The obtained results are better than those of other approaches [11,14,17,18,42,44–46] in terms of both sensitivity and specificity. It should be mentioned that most of the previously reported methods measured an ST segment with fixed lengths after pointJ, whereas the proposed method takes window lengths depending on the RR interval. The methods mentioned above have their own advantages and disadvantages. For example, digital analysis techniques [5,6,16] are easy to implement in real time. Similarly, rule based algorithms [45] provide an exact decision as with that of experts. A limitation of this methodology is the requirement of a representative training set in order to extract reliable rules for validation. HMM [12] achieves the best average statistics in ischemic episode detection, but is not suitable for non-ischemic episode detection. Fuzzy logic [14,20] based systems have great importance in the diagnosis of ischemia in terms of validating the rules, but still need further investigation in order to improve the diagnosis performance. Neural network based systems [42,43] can detect ischemia more reliably than can other existing systems but are not able to provide an interpretation of a diagnosis because of the black box nature of hidden layers. In the same way, genetic algorithm [11], support vector machine, kernel density estimation [18] and multi-criteria decision analysis [44] based algorithms take more time for decision as they involve many complex calculations for the optimization process. This paper has relevance to ST segment area and deviation based methods [47–49], to distinguish ischemic from normal ST segments. We have measured isoelectric energy based on ST segment deviations and could also employ additional morphological features of ST segments. The proposed method has two major advantages. The method can provide an interpretation of results. This is of great importance in designing a medical support decision device. This would also help with patients in a CCU without knowing past references. Second, it involves direct analysis based on isoelectric energy without the involvement of any complicated algorithm. In Table 1, the results are compared in terms of sensitivity and specificity with the existing methods for the European ST-T database. Filtering and delineation have been performed in a well-organized manner, which makes it possible to attain significantly better results than those of existing methods. The disadvantage of the proposed method is that it is not applicable to analyze T waves for ischemia detection. Furthermore, in order for the described method to be used in clinical practice, the database records should be extended and additional types of ischemic and normal ECG waveform patterns should be included.

6. Conclusion and future scope

We have successfully proposed and validated a simple method for the diagnosis of ischemia based on a threshold of isoelectric energy of ST segments in ECG signals. The multi-resolution features of a wavelet transform have been employed for the pre-processing and delineation of ECG characteristic points. The proposed method achieves significantly better results than do the existing methods in the literature. The method does not involve any complex calculations and could also employ additional morphological features of ST segments. The increasing demand for the achievement of higher sensitivity, specificity and predictivity values is still challenging for researchers. The future scope includes possible remarkable results in terms of performance and capabilities with respect to standard databases using a combination of promising techniques.

Conflict of interest statement

The authors have nothing to declare.

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